MSc Thesis Finance

Momentum Strategies for Asset Classes

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Abstract

Inspired by the paper of Moskowitz, Ooi, and Pedersen (2012) and Kolanovic & Wei (2015), this study investigates the effect of time-series momentum across the asset classes: equity, bonds, commodities, and currencies. The performance for each time-series momentum strategy is measured by its Sharpe ratio and alpha. The results show that time-series momentum strategies are the most effective with frequent rebalancing because the highest average Sharpe ratios are found for strategies with holding periods of 1- or 3-months (see table 1). Based on alpha as a performance measure, the highest estimated annualized alphas are found for equity (see table 2). For the asset class equity, the annualized alpha reaches a value of 8.603% (a strategy with a look-back period of 6 months and a holding period of 6 months). The computed alphas for the asset classes equity and bonds show that for most strategies the annualized alpha is positive and significant, which indicates that the use of time-series momentum strategies leads to abnormal returns. For the asset classes' commodities and currencies, strategies with holding periods of 6- and 12-months deliver negative alphas.

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1. Introduction

Is it possible for an investor to use time-series momentum strategies to generate competitive Sharpe ratios and abnormal returns, across asset classes? Momentum strategies have been a very controversial subject among academics and investors. The main research question of this thesis is: to what extent can time-series momentum strategies generate competitive Sharpe ratios and abnormal returns, across the four asset classes: equity, bonds, commodities, and currencies? The profitability of the time-series momentum strategies will be measured by two different performance measures, the Sharpe ratio, and alpha. The Sharpe ratio will be used as a tool to assess the performance of an asset class. The Sharpe ratio adjusts a portfolio's past performance, for the excess risk that was taken. The higher the Sharpe ratio is for an asset class the better the performance of this asset class is. Next to the Sharpe ratio, the alpha will be analyzed. Alpha will also be used as a measure of performance, it indicates whether a strategy has managed to beat the market return over a given period. The excess return of a strategy relative to the return of a benchmark index is the alpha.

Equity was the first asset class in which evidence for momentum was documented, this was done by Jegadeesh and Titman (1993). The method that was used in their paper became a very popular methodology for composing momentum portfolios. After the paper of Jegadeesh and Titman (1993), new papers about momentum strategies were published in which momentum was also documented for other asset classes. Erb & Harvey (2006) and Miffre & Rallis (2007) documented momentum effects for commodities. Furthermore, Menkhoff et al. (2012) documented momentum effects for the asset class currencies. Only for the asset class fixed income, there is almost no existing literature available. A paper that discussed momentum in bond markets, is the paper of Luu and Yu (2012).

Time-series momentum strategies are economically important because if investors can gain profit from time-series momentum strategies at the asset class level, this will result in higher financial benefits to investors than a regular buy and hold strategy. What element in this thesis goes beyond existing work? Existing studies that investigated momentum strategies are mostly about futures or focusing on one specific asset class, this study will investigate time-series momentum strategies for four different asset classes: equity, bonds, currencies, and commodities. Can the time-series momentum effect also be proven to exist within various other asset classes like bonds, commodities, and currencies? This will be investigated in this paper. Next to that, this paper also uses a different percentage for volatility scaling, than most existing papers. Most papers that documented time-series momentum used 40% in their formula for the volatility calculation, but this 40% is not based on anything. In this paper there is chosen to use the average volatility of the asset class as N. We will investigate if there are different results found with this method.

The remainder of this thesis is organized as follows: chapter 2 will provide a literature review on momentum strategies. Chapter 3 goes more in detail on which data is being used. Chapter 4 explains the methodology that is used. Furthermore, the results and outcomes are discussed in chapter 5. Finally, chapter 6 summarizes the paper and a conclusion will be given.

2. Literature review

2.1. Momentum in equity markets

Momentum strategies have been a very controversial subject among academics and investors. Jegadeesh & Titman (1993) were one of the first academics that researched momentum strategies. They examined some momentum strategies and document that strategies, which buy stocks with higher returns over the previous 3 to 12 months and sell the stock with poor returns over the same period earn profits of about one percent per month for the following year. Jegadeesh & Lakonishok found evidence that the momentum strategy results in a higher profit for investors. “We evaluated the profitability of price momentum strategies based on past return and earnings momentum strategies based on standardized unexpected earnings and revisions of consensus forecasts. The strategies proved to be profitable for intermediate horizons. Chasing momentum can generate high turnover”, Jegadeesh & Lakonishok (1996). Jegadeesh & Lakonishok implemented cross-sectional momentum strategies, this will paper will focus on time-series momentum strategies, because from the existing literature review there can be concluded that time-series momentum is superior to cross-sectional momentum. “We find that over our sample period, both types of momentum strategies generate positive returns under the majority of implementations evaluated but that time-series momentum is superior. An important difference between the two momentum strategies is that with time-series momentum, the number of stocks included in the winner and loser portfolios varies with the state of the market. As a consequence, cross-sectional momentum digs deeper to select winning stocks when markets are weak and deeper to select losing stocks when markets are strong. As the information in the momentum signals is concentrated in the tails of the return distribution, it is not that surprising that momentum is best implemented using time-series momentum, “(Bird, Gao &Yeung (2016)). Another major advantage of time-series momentum is that it could be useful in weaker states of the economy. Several researchers have shown that these time-series momentum strategies could predict if there is a crisis coming for a given asset class. So if the strategy would predict a crisis, it would push the investor from the market or it would indicate a short opportunity for the investor. Since there is already proven that time-series momentum is superior I chose to focus on time-series momentum in this paper.

So what is time-series momentum exactly? Kolanovic & Wei (2015) define time-series momentum strategies as follows: “Time-series momentum strategies use trend indicators to determine the price trends of each asset individually, based on which a long (or short) position is established. An example is to use a simple 12-month price return: go long an asset with positive 12-month return; stay in cash (or short) asset with a negative 12-month return."

Another interesting conclusion was made by the paper of He & Li (2015). In their paper, they showed that the performance of momentum strategies is determined by the time horizon and the market dominance of momentum traders. "Specifically, when momentum traders are more active in the market, momentum strategies with short (long) time horizons stabilize (destabilize) the market, and meanwhile the market under-reacts (over-reacts) in short-run (long-run). This provides profit opportunity for time-series momentum strategies with short horizons and reversal with long horizons", He & Li (2015).

2.2. Momentum in bonds markets

The amount of literature about momentum in bond markets is very limited. A paper that discussed momentum in bond markets, is the paper of Luu and Yu (2012). They explored the risk-return properties of simple momentum strategies in six major government-bond markets and they concluded that momentum within government bonds resulted in significant abnormal returns.

2.3. Momentum in commodities

A paper that focused on momentum in the asset class commodities is the paper of Erb & Harvey (2006). They showed that a momentum strategy with a 12-month ranking period and a 1- month holding period is profitable in commodity futures markets. Another paper that focused on time-series momentum in the commodity markets is the paper of Miffre & Rallis (2007). "13 momentum strategies are found to be profitable in commodity futures markets over horizons that range from 1 to 12 months. Our tactical allocation in commodity futures markets generates an average return of 9.38% a year. Interestingly, a portfolio that equally weights the 31 commodity futures considered in the study lost 2.64% a year over the same period", Miffre & Rallis (2007). Miffre & Rallis concluded that momentum returns of commodities cannot be described as compensation for exposure to risks. Both the paper of Erb & Harvey and the paper of Miffre & Rallis (2007) concluded that there is evidence that momentum strategies work only on the short term for the asset class commodities. On the long term both papers found a reversal in commodity futures prices.

2.4. Momentum in currency markets

There are quite some papers that have shown the success of implementing momentum strategies in the foreign exchange market. One of these papers is from Menkhoff et al. (2012), who provided a broad empirical investigation of momentum strategies in the foreign exchange market. In their research, they found large and significant excess returns to currency momentum strategies of up to 10% per annum. “In summary, we provide evidence that, despite FX markets' differences relative to stock markets, the properties of momentum strategies are fairly similar, which suggests that momentum profits in different asset classes could share a common root,” Menkhoff et al. (2012). They also concluded that momentum strategies are risky because their return is unstable over short periods and next to that their exposure is also subject to some fundamental investment risk.

2.5. Momentum among different asset classes

Most existing research documented momentum strategies only on one asset class, like equity or commodities. One of the few papers that found evidence for momentum strategies at different asset classes is the paper of Moskowitz, Ooi, & Pedersen (2012).“We find persistence in returns for 1 to 12 months that partially reverses over longer horizons, consistent with sentiment theories of initial under-reaction and delayed over-reaction. A diversified portfolio of time-series momentum strategies across all asset classes delivers substantial abnormal returns with little exposure to standard asset pricing factors and performs best during extreme markets”, Moskowitz, Ooi, & Pedersen (2012). They provided evidence of the existence of time-series momentum concerning future markets.

Another paper that found evidence for momentum strategies at different asset classes is the paper of Asness, Moskowitz, and Pedersen (2013). “We provide comprehensive evidence on the return premia to value and momentum strategies globally across asset classes, and uncover strong common factor structure among their returns,” Asness, Moskowitz, and Pedersen (2013).

Furthermore, the study of Hurst, Ooi, and Pedersen (2013) explains the returns of Managed Future funds by time-series momentum strategies. In their study, they considered multiple implementation issues which could be relevant to time-series momentum strategies. Including risk management, risk allocation across asset classes and trend horizons, portfolio rebalancing frequency, transaction costs, and fees. They found a very competitive Sharpe ratio of 1.8, for a diversified time-series momentum strategy. The conclusion that can be made up from the paper of Hurst, Ooi, and Pedersen (2013): "investors can get exposure to Managed Futures using time-series momentum strategies, and should pay attention to implementation issues such as fees, trading infrastructure, and risk management procedures used by different managers."

3. Data description

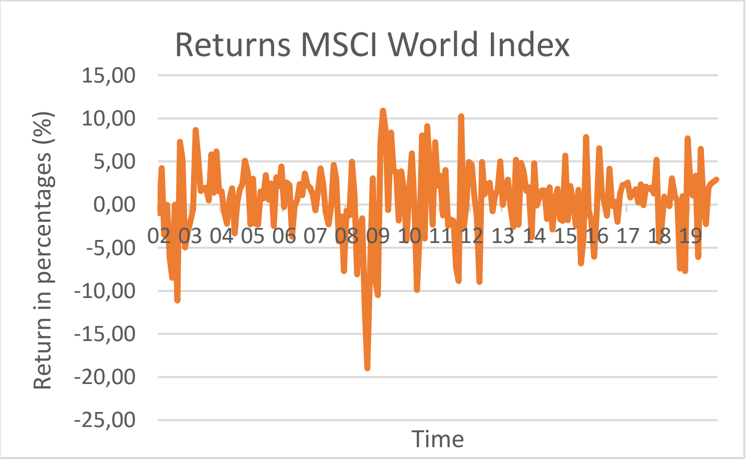
The dataset that is used in this paper consists of monthly prices of the following four asset classes: equity, bonds, currencies, and commodities. The data covered the period from 01.01.2002 till 31.12.2019. The prices for the four asset classes are denominated in dollars.

The data that is used for the asset class equity is represented by the MSCI World index. The MSCI World index is an international equity index, which tracks stocks from 23 developed countries. The following developed countries are represented by the MSCI world index: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the UK, and the US. The choice for these equity markets is based on the paper of (Asness, Moskowitz, & Pedersen, 2013). The monthly prices of the equity indices are retrieved from Eikon. In the table below the descriptive statistics of the MSCI World Index can be found.

Descriptive statistics MSCI World Index	
Mean	1429,615454
Standard Error	26,79898672
Median	1370,035
Standard Deviation	393,8630585
Kurtosis	-0,73792412
Skewness	0,315779296
Range	1620,29
Minimum	738,18
Maximum	2358,47

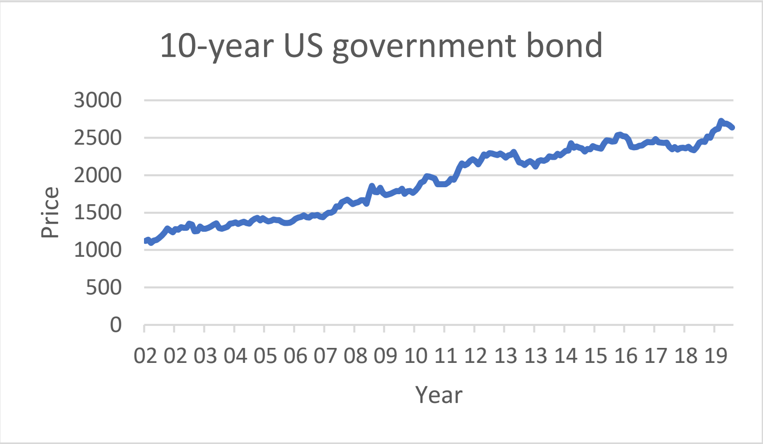
In the table below the descriptive statistics of the returns of the MSCI World Index are given:

Descriptive statistics returns	
Mean	0,50420889
Standard Error	0,288884863
Median	1,067063074
Standard Deviation	4,235883591
Kurtosis	2,214358996
Skewness	-0,818592314
Range	29,89561825
Minimum	-18,99176589
Maximum	10,90385236



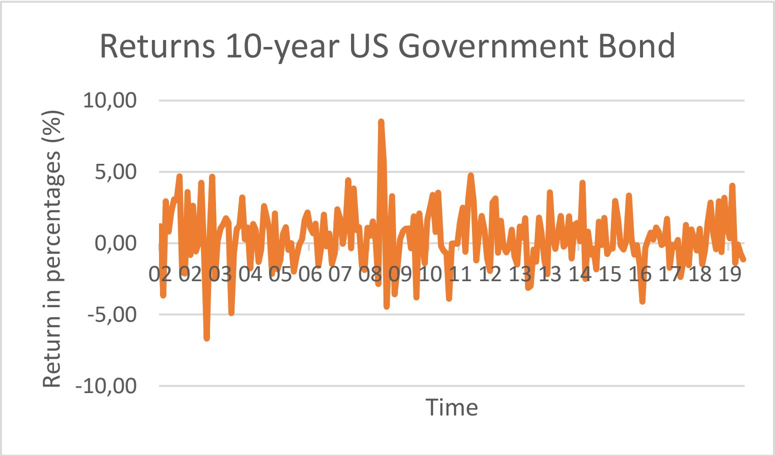
The data that represents the asset class bonds consists of the 10-year government bond from the US. Unfortunately, there was no access to get the data for the FTSE world government bond index, so there is chosen to use the data from the US. The data for these government bonds are retrieved from Eikon. In the table below the descriptive statistics of the 10-year government bond of the US can be found

Descriptive statistics 10-year US government bond	
Mean	1909,063
Standard Error	31,53846
Median	1928,449
Standard Deviation	463,5188
Kurtosis	-1,47511
Skewness	-0,11655
Range	1630,977
Minimum	1094,637
Maximum	2725,614



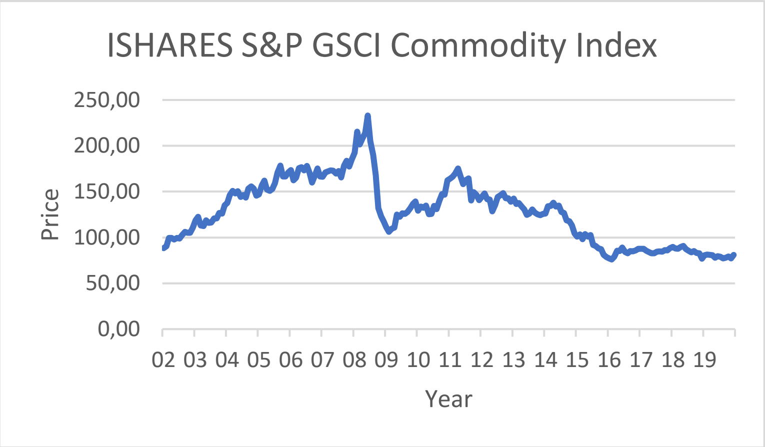
In the table below the descriptive statistics of the returns of the 10-year US government bond are given:

Descriptive statistics returns	
Mean	0,417436
Standard Error	0,136313
Median	0,280409
Standard Deviation	1,998737
Kurtosis	1,510788
Skewness	0,119576
Range	15,21972
Minimum	-6,68192
Maximum	8,537799



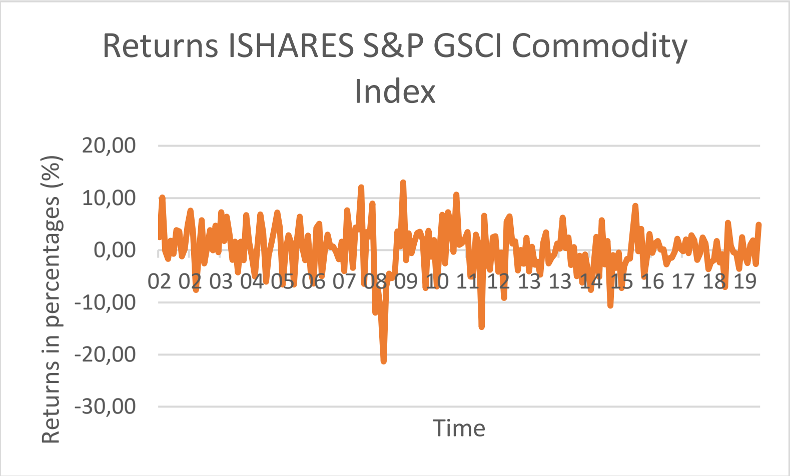
The data that is used for the asset class commodities are represented by the ISHARES S&P GSCI Commodity index. The ISHARES S&P GSCI Commodity index seeks to track the results of a fully collateralized investment in futures contracts on an index composed of a diversified group of commodities futures. In the table below the descriptive statistics of the ISHARES S&P GSCI Commodity index can be found.

Descriptive statistics ISHARES S&P GSCI Commodity index	
Mean	127,87147
Standard Error	2,3789225
Median	127,79865
Standard Deviation	34,962878
Kurtosis	-0,628597
Skewness	0,2946397
Range	157,0877
Minimum	75,9463
Maximum	233,034



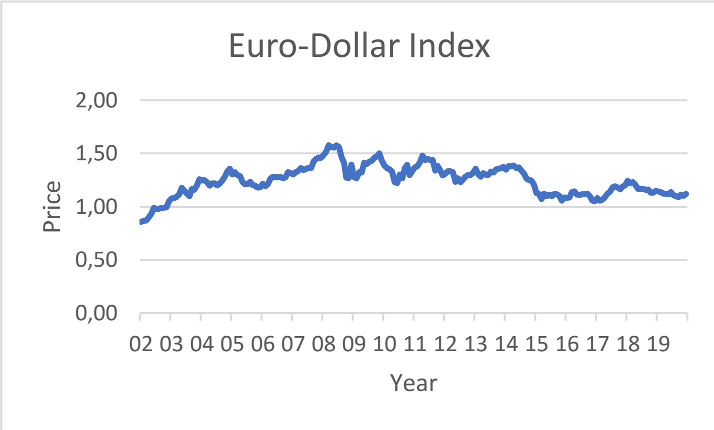
In the table below the descriptive statistics of the returns of the ISHARES S&P GSCI Commodity Index are given:

Descriptive statistics returns	
Mean	0,0653479
Standard Error	0,3116011
Median	0,2935154
Standard Deviation	4,5689685
Kurtosis	2,3127621
Skewness	-0,570775
Range	34,328393
Minimum	-21,34036
Maximum	12,988035



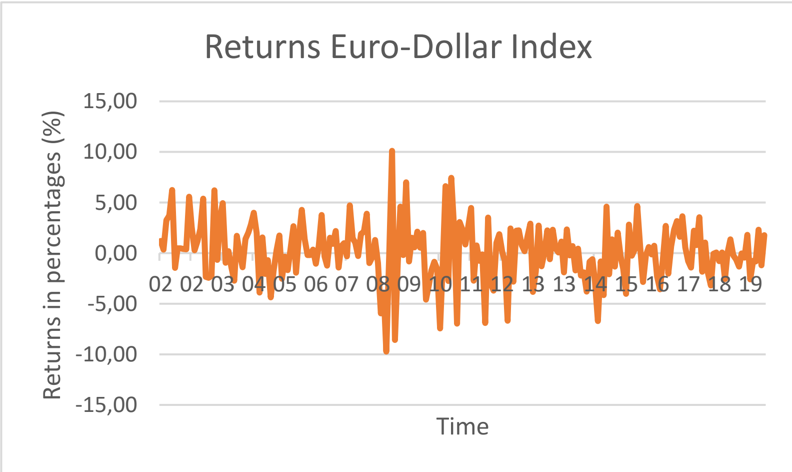
The data that is used for the asset class currencies consists of the spot exchange rates dollar and euro. The spot exchange rates are retrieved from Eikon. In the table below the descriptive statistics of the Euro-Dollar index can be found.

Descriptive statistics Euro-Dollar Index	
Mean	1,243918056
Standard Error	0,009571865
Median	1,2477
Standard Deviation	0,140677113
Kurtosis	-0,1028811
Skewness	-0,0965587
Range	0,719
Minimum	0,8582
Maximum	1,5772



In the table below the descriptive statistics of the returns of the Euro-Dollar Index are given:

Descriptive statistics returns	
Mean	0,163957462
Standard Error	0,192139823
Median	0,14259982
Standard Deviation	2,817322845
Kurtosis	1,535493597
Skewness	-0,1768331
Range	19,83545752
Minimum	-9,72911644
Maximum	10,10634108



This study is about excess returns, the risk-free rate is needed to compute the excess returns. The 3-month U.S. Treasury Bill is considered as the risk-free rate for this study. The risk-free rate is downloaded from WRDS. The excess returns are computed by subtracting the risk-free rate from the return.

4. Time-Series Momentum Strategies – Methodology

Time-series momentum is an efficient way to predict patterns. An important role for tactical asset allocation is to understand which asset class will perform better "the next day". Which results in underweighting some asset classes and on the other side overweighting other asset classes. In this study, transaction costs are not taken into consideration, since they won't play a massive role in the conclusion of the study. Nowadays, there are quite some ETFs that can be purchased with very low transaction costs.

Construction of the time-series momentum strategies

The trading signals that are used for the time-series momentum strategies are derived from cumulative past returns. If the cumulative past return is positive, the future returns are also expected to be positive because of the trend-following patterns. So this means that for a positive cumulative return, the market signal will be a "buy". When the cumulative past return is negative, the future returns are also expected to be negative. In this case, the market signal will be a "sell".

This study will vary in both the number of months we lag returns to define the signals used to form the portfolio (the "look-back period") and the number of months each portfolio is held after it has been formed (the "holding period"). Each strategy has a different look-back period and holding period. By changing these three elements, different trading strategies are formed. This study considers four different look-back periods (k): 1, 3, 6, and 12 months. The look-back period will indicate how many past months are included in the calculation of the cumulative returns. So, a look-back period of k implies that the cumulative returns are the sum of the past k returns. On the other hand, this study will also vary in the number of months the portfolio will be held. Four different holding periods (h) are taken into consideration: 1, 3, 6, and 12 months. The trading signal does not change during the holding period. The combination of the number of look-back periods and the number of holding periods will give 16 different strategies. The 16 strategies can be examined with two different approaches: with or without short-selling constraints. Going short on an asset could give an investor some extra profits, but on the other hand, short-selling also increases the overall risk of a portfolio. In this paper, all the strategies are considered with short-selling possibilities. The expectation is that momentum will perform better in the shorter holding periods, so the 1- and 3-month holding periods. This is because in these shorter holding periods the portfolio gets rebalanced frequently.

After the trading signals are computed for each asset class, the final portfolio is made. There will be four different portfolios: equity, bond, commodity, and currency. For building the portfolios, it is essential to give weights to all the assets. There are two approaches to give weights to the assets: the equally weighted approach and the volatility scaling approach that was used by the paper of Moskowitz, Ooi, and Pedersen (2012). This thesis will only investigate the volatility scaling approach, due to the fact to the fact that recent papers concluded that time-series momentum is more successful when the volatility approach of Moskowitz, Ooi, and Pedersen (2012) is being used. For example, the paper of Kim, Tse, and Wald (2016) confirms the choice for the volatility scaling approach: “Using TSMOM, the alphas of the individual contracts are on average 1.08%, the same as the portfolio alpha. However, if we use unscaled, equal-weighted returns, the portfolio alpha, and the average individual alpha drop to 0.39% and 0.40%, respectively.” So a volatility scaling approach seems to be superior to the equally weighted approach.

Volatility scaling approach

The volatility scaling approach that will be investigated is comparable to the approach of Moskowitz (2012). Moskowitz, Ooi, and Pedersen (2012) sized each position so it had ex-ante volatility of 40%. In this approach, the weights across the assets won’t be constant, the weight of an asset is negatively related to volatility. The size of a position increases (decreases) when the volatility of an asset is smaller (larger). The reason why there is chosen for this approach is that otherwise the analysis would be driven by high volatility asset classes. The strategy return for each asset will be determined as follows:

$$r_{t,t+h}^{TSMOM,s} = sign\left(r_{t-k,t^s}\right) * \frac{N\%}{\sigma_t^s} * r_{t,t+h^s}$$

Where $r_{t,t+h}^{TSMOM,s}$ represents the momentum strategy excess return of asset s at time t. k is the number of months considered as the look-back period and h is the number of months considered as the holding period. N% is the ex-ante volatility. Most papers that documented time-series momentum used 40% in their formula for the volatility calculation, but this 40% is not based on anything. In this paper it was chosen to use the average volatility of the asset class as N. We will investigate if there are different results found with this method.

$$\sigma_t^2 = 12 * \sum_{i=0}^{\infty} * (1-\theta) * \theta^i * (r - \bar{r}_t)^2$$

Where $\sigma_t{}^2$ represents the annualized variance for each asset class. The scalar 12 makes the volatility annual and Θ represents the rate of decay. The weights $(1-\theta)*\theta^i$ add up to one, and $\overline{r_t}$ is the exponentially weighted average return. The volatility model is the same for all assets at all times.

Every strategy will be tested on each asset class (equity, bond, commodity, and currency). The constructed strategies will be analyzed by two different performance measures. The Sharpe Ratio and alpha.

4.1. Performance Measure 1: Sharpe Ratio

The Sharpe ratio adjusts a portfolio's past performance, for the excess risk that was taken. The higher the Sharpe ratio is for an asset class the better the performance of this asset class is.

The Sharpe Ratio is calculated by dividing the average annualized excess return by the average annualized volatility. Where the volatility is the standard deviation of the returns.

$$Sharpe\ ratio = \frac{R_p - R_f}{\sigma_p}$$

Where, R_p is the return of portfolio, R_f is the risk-free rate and σ_p is the standard deviation.

4.2. Performance Measure 2: Alpha

The ability for an investor to get an additional return without increasing risk, cannot be measured with the Sharpe Ratio. To find out if this is possible we need to compute the alpha from a benchmark regression. Of course, it will be possible to increase the profitability of a portfolio by increasing risk, but that is not the purpose of this study. A standard approach that is being used in literature to adjust risk performance is to regress the returns of a certain strategy on the Fama-French 3 factor model. This study differentiates from this standard approach since this study is not only about equity, there are more asset classes involved. The factors SMB (small minus big) and HML (high minus low) will be excluded and some new factors will be added. SMB is a factor in the Fama/French pricing model that says smaller companies outperform larger ones over the long-term. HML is another factor in the model that says value stock tend to outperform growth stocks. Moskowitz et all. (2012) didn't find any significant betas for SMB or HML, that is the reason why this paper also excludes these factors.

Alpha is a term used to describe an investment strategy's ability to beat the market and it is often referred to as "excess return" or "abnormal rate of return", which refers to the idea that markets are efficient, so there is no way to systematically earn a return that exceeds the market. Alpha represents the performance of a portfolio relative to a benchmark, so alpha represents the extra value time-series momentum adds to the return. A positive and significant alpha would mean that the time-series momentum strategy provides an additional return. To evaluate the abnormal performance of the time-series momentum strategies, the alphas will be computed from the following regression:

$$r_t^{TSMOM(k,h)} = a + \beta 1 * \mathrm{MKT} + \beta 2 * \mathrm{BOND} + \beta 3 * \mathrm{GSCI} + \beta 4 * \mathrm{USDX} + \varepsilon,$$

where k is the look-back period and h the holding period. In the regression, the dependent variable is an excess return of the trading strategy with k look-back periods and h holding periods. The independent variables represent coefficients for the market factor (MKT), the bond index (BOND), commodity index (GSCI), and the currency index (USDX). These regressors are the times series of the chosen asset classes that are explained in chapter 3.

5. Time-Series Momentum Strategies – Results

When using a time-series momentum strategy an investor takes a long or short position based on an asset's recent performance over some look-back period. For example a look-back period of 12 months. Every month an investor considers whether the excess return of each asset over the past 12 months is positive or negative. An investor will go long if this excess return over the past 12 months is positive and the investor will go short if this excess return over the past 12 months is negative. The position that the investor will take depends on the volatility. In this paper we investigated different holding periods. When for example the holding period is 12 months, the investor sells his portfolio after 12 months. The reported results are over a rolling window depending on the look-back period and holding period of the strategy. A rolling window is expressed relative to the date and automatically shifts forward if time passes. In the example of the 12 month holding period, first the data covers the period for January 2002 till January 2003. The static window rolls forward and two months later the rolling window will cover the period from March 2002 till March 2003.

In order to implement the analysis of the momentum strategy, I used Stata 16. All the codes ran on an Intel Core i5.

5.1. Performance Measure 1: Sharpe Ratio – Results

The performance of the constructed strategies is analyzed by their Sharpe ratios. The Sharpe ratio is calculated by dividing the annualized excess return by the average annualized volatility during the sample. The volatility is calculated as the standard deviation of the returns. The EWMA estimator of volatility is used.

The Sharpe ratio uses the standard deviation to measure the risk-adjusted returns for an asset. The greater the Sharpe ratio of an asset, the better its risk-adjusted-performance. A negative Sharpe ratio would indicate that either the risk-free rate is greater than the return of the asset, or the return of the asset is expected to be negative.

Intuitively, one could say that the Sharpe ratio of a risk-free asset is zero. So a positive Sharpe ratio would therefore indicate a higher reward for risk. The higher the Sharpe ratio, the better the investment looks from a risk/return perspective.

Table 1: Average Sharpe ratios for strategies with different holding periods

The period taken into consideration is 01.01.2002 till 31.12.2019.

Holding period (in months)	Asset Class	Average Sharpe ratio
1	Equities	0.24
1	Bonds	0.18
1	Commodities	0.23
1	Currencies	0.30
3	Equities	0.22
3	Bonds	0.24
3	Commodities	0.15
3	Currencies	0.08
6	Equities	0.18
6	Bonds	0.16
6	Commodities	-0.01
6	Currencies	-0.03
12	Equities	0.08
12	Bonds	0.11
12	Commodities	-0.14
12	Currencies	-0.19

The results in table 1 show that frequently rebalancing is very important. Strategies with shorter holding periods have a higher average Sharpe ratio compared to the strategies with longer holding periods. The highest Sharpe ratios are found for strategies with holding periods of 1 month and the lowest Sharpe ratios are found for strategies with holding periods of 12 months. For the Sharpe ratios, the significance is not taken into consideration, the formal significance test is only done for the annualized alphas.

An overview of the computed Sharpe ratios and the descriptive statistics per strategy are given in the appendix.

<u>Results per asset class</u>

Equity: The Sharpe ratio for the benchmark of equity is 0.33 (see table A5), a Sharpe ratio higher than 0.33 would indicate that momentum strategies are beneficial for the asset class equity. The strategy that gives the most competitive Sharpe ratio for equity, is a strategy with a look-back period of 6 months and a holding period of 1 month (see table A1).

Time-series momentum strategies provide competitive Sharpe ratios for the asset class equity, but only for shorter holding periods. For strategies with holding periods of 6- or 12 months, the results show a lower Sharpe ratio than the benchmark (see tables A3 & A4). The results for equity are in line with the paper of He & Li (2015), they also concluded that time-series momentum offers profit opportunity for strategies with shorter holding periods and tend to reverse for strategies with longer holding periods.

Bonds: The Sharpe ratio for the benchmark of bonds is 0.34 (see table A5), a Sharpe ratio higher than 0.34 would indicate that momentum strategies are beneficial for the asset class bonds. The strategy that gives the most competitive Sharpe ratio for bonds, is a strategy with a look-back period of 12 months and a holding period of 3 months (see table A2).

Current literature about time-series momentum on bonds is very scarce. An interesting conclusion that can be made is that for some strategy combinations time-series momentum can be successful for the asset class bonds. For example, the strategy with a look-back period of 12 months and a holding period of 3 months, gives a competitive Sharpe ratio of 0.45 (see table A2). But that are also quite some strategies that generate a lower Sharp ratio for bonds. This could be due to short-term return reversal. "Short-term reversal is the cross-sectional, negative relation between current stock returns and lagged returns", Kang, Khaksari & Nam (2018). The fact that, if a bond portfolio is giving negative past cumulative returns for some time, the returns could revert very quickly. This characteristic of bonds is not captured by time-series momentum strategies. Especially short positions could lead to potential losses, which hurts the returns of the bond portfolio.

Commodities: The Sharpe ratio for the benchmark of commodities is -0.04 (see table A5), a Sharpe ratio higher than -0.04 would indicate that momentum strategies are beneficial for the asset class commodities. The strategy that gives the most competitive Sharpe ratio for the asset class commodities, is a strategy with a look-back period of 3 months and a holding period of 1 month (see table A1).

The use of time-series momentum leads to some competitive Sharpe ratios for the asset class commodities, but only for time-series momentum strategies with shorter holding periods. Especially for the strategies with holding periods of 1-, 3- months successful Sharpe ratios are found (see tables A1 & A2). Similar results are found in the paper of Erb & Harvey (2006), who concluded that a momentum strategy with a 12-month ranking period and a 1- month holding period is profitable in commodity futures markets. The outcomes for commodities are also in line with the paper of Miffre and Rallis (2017). They found 13 momentum strategies that were profitable in commodity futures markets over horizons that range from 1 to 12 months. Miffre and Rallis stated that there is a short-term continuation and long-term reversal in commodity futures prices.

Currencies: The Sharpe ratio for the benchmark of currencies is 0.06 (see table A5), so a Sharpe ratio higher than 0.06 would indicate that momentum strategies are beneficial for the asset class currencies. The strategy that gives the most competitive Sharpe ratio for the asset class commodities, is a strategy with a look-back period of 3 months and a holding period of 1 month (see table A1).

The results show that momentum strategies can be successful for currencies. Especially strategies with shorter holding periods give competitive Sharpe ratios. This outcome is in line with the evidence Moskowitz et al. (2012) provided. They also concluded that time-series momentum strategies for currencies are profitable.

An important role in momentum strategies is rebalancing. Beforehand the expectation was that the strategies which are frequently rebalanced would have the highest Sharpe ratios. This is also the case. The results reported in table 1 show that time-series momentum strategies with a holding period of 1- and 3-months have on average the highest Sharpe ratios. The momentum strategies with a holding period of 12 months have on average the lowest Sharpe ratios.

The conclusion that can be made up from the results is that time-series momentum strategies deliver competitive Sharpe ratios, but there are strategies that provide a lower Sharpe ratio compared with the benchmark. The results show that time-series momentum strategies work better for shorter holding periods (1- and 3-months). Strategies with holding periods of 12 months all perform worse than the benchmark, so when a time-series momentum strategy is implemented one is better off by choosing for a shorter holding period. Momentum strategies are mainly effective with frequent rebalancing. The most profitable strategies have a holding period of 1- or 3-months.

These competitive Sharpe ratios are not the only advantage of time-series momentum. Time-series momentum also takes away some risk. For example, a crisis could occur, which would have a negative influence on the market. A momentum strategy would push the investor out of the market, it would prevent an investor from losses. When short-selling is used like in this study, an investor would sell losing assets in a crisis, which could provide high returns. So there can be concluded that next to the competitive Sharpe ratios, time-series momentum also takes some risks away from the investor.

5.2. Performance Measure 2: Alpha – Results

Alpha represents the performance of a portfolio relative to a benchmark, so alpha represents the extra value time-series momentum adds to the return. A positive and significant alpha would indicate that time-series momentum strategies provide additional returns. To evaluate the abnormal performance of the strategies, the alphas are computed from the following regression:

$$r_t^{TSMOM(k,h)} = a + \beta 1 * \mathrm{MKT} + \beta 2 * \mathrm{BOND} + \beta 3 * \mathrm{GSCI} + \beta 4 * \mathrm{USDX} + \varepsilon$$

In the regression, the equity benchmark is represented by the MSCI world index. The bond benchmark is represented by the US 10Y Govt Bond. Furthermore, the ISHARES S&P GSCI Commodity-index represents the commodity benchmark and the currency benchmark is represented by the US dollar index.

Table 2: Annualized alphas

The reported annualized alphas are computed from the following regression: $r_t^{TSMOM(k,h)} = a + \beta 1 * \mathrm{MKT} + \beta 2 * \mathrm{BOND} + \beta 3 * \mathrm{GSCI} + \beta 4 * \mathrm{USDX} + \varepsilon$. *In this regression, the equity benchmark is represented by the MSCI world index. The bond benchmark is represented by the US 10Y Govt Bond. Furthermore, the ISHARES S&P GSCI Commodity-index represents the commodity benchmark and the currency benchmark is represented by the US dollar index. The annualized alphas are expressed in percentage points. TSMOM(k,h), stands for time-series momentum strategy with a look-back period of k and a holding period of h.*

Strategy	Equities	Bonds	Commodities	Currencies
TSMOM (1,1)	2.534**	-1.579***	3.823***	2.289**
TSMOM (3,1)	5.134***	1.825***	4.765***	5.296***
TSMOM (6,1)	5.427***	1.245**	5.990***	4.272***
TSMOM (12,1)	3.651***	2.338***	3.888***	1.960***
TSMOM (1,3)	3.127**	0.105	3.927***	1.846***
TSMOM (3,3)	4.541***	2.244***	6.668***	4.123***
TSMOM (6,3)	3.896***	0.277	3.609***	1.493**
TSMOM (12,3)	6.064***	3.093***	-3.717***	-2.531***
TSMOM (1,6)	5.276***	0.749	0.093	1.958***
TSMOM (3,6)	5.896***	2.094***	5.956***	2.199***
TSMOM (6,6)	8.603***	1.775***	-0.961	-2.567***
TSMOM (12,6)	4.455**	2.075***	-3.790**	-2.577***

TSMOM (1,12)	5.014***	0.938*	-3.331**	-1.371**
TSMOM (3,12)	4.705***	1.072**	-4.413***	-1.711**
TSMOM (6,12)	7.150***	0.948*	-5.623***	-3.114***
TSMOM (12,12)	4.273**	2.653***	-4.645***	-2.326***

*** p<0.01, ** p<0.05, * p<0.1

The results show that for most strategies the annualized alpha is positive and significant, which indicates that the use of time-series momentum strategies leads to abnormal returns. Especially most strategies with holding periods of 1- and 3-months, give positive and significant annualized alphas. Furthermore, it is interesting to see that especially for the asset classes' commodities and currencies the strategies with holding periods of 6- and 12-months deliver negative and significant annualized alphas. So there can be concluded that it is very important for an investor to frequently rebalance his or her portfolio, especially for the asset classes' commodities and currencies. The use of time-series momentum strategies on commodities and currencies is only successful when an investor is frequently rebalancing. Otherwise, the use of time-series momentum strategies leads to losses for the investor. Strategies with a holding period of 12 months only show negative and significant alphas for commodities and currencies, which indicates a reversal in returns for these asset classes.

The results show that in most cases time-series momentum strategies are successful since most strategies deliver positive and significant annualized alphas. Time-series momentum strategies work the best for equity since for equity the highest positive and significant alphas are found. Bonds, commodities, and currencies also deliver some positive and significant alphas but in comparison with equity, these asset classes are underperforming.

For the asset class equity, the annualized alpha reaches a value of 8.603% (a strategy with a look-back period of 6 months and a holding period of 6 months). The bond's alpha reaches a value of 3.093% (a strategy with a look-back period of 12 months and a holding period of 3 months. For the asset class commodities, an annualized alpha of 6.668% is found (a strategy with a look-back period of 3 months and a holding period of 3 months). The alpha of currencies reaches an annualized alpha of 5.296% (a strategy with a look-back period of 3 months and a holding period of 1 month).

Moskowitz et all. (2012) found a significant alpha of 1.58% per month or 4.75% per quarter. So in comparison with the study of Moskowitz et all. (2012) this study delivers a lower alpha, this could be because in this study a lower N is used for the volatility calculation. Moskowitz et all. (2012) used an N of 40%, whereas in this study there is chosen to use the average volatility of each asset class as N.

More detailed results of the annualized alphas can be found in part B of the appendix. For each strategy, the coefficients of the regression, the standard deviations, and the R-squared are reported in this part.

6. Conclusion

This study investigated to what extent time-series momentum strategies could generate competitive Sharpe ratios and abnormal returns, across the four asset classes: equity, bonds, commodities, and currencies. The profitability of the time-series momentum strategies was analyzed by their Sharpe ratios and alphas. Where the Sharpe ratio adjusted a portfolio's past performance, for the excess risk that was taken. The alphas indicated whether a strategy manages to beat the market return over a given period. Alpha represents the excess return of a strategy relative to the return of a benchmark index.

Momentum strategies have been a well-researched topic by academics and investors. Jegadeesh and Titman (1993) were one of the first authors who documented price continuation for the asset class equity and their method became a very popular methodology for composing momentum portfolios. Momentum strategies were also investigated for other asset classes. Erb & Harvey (2006) and Miffre & Rallis (2007) documented momentum effects for commodities. Furthermore, Menkhoff et al. (2012) documented momentum effects for the asset class currencies. Only for the asset class fixed income, there is almost no existing literature available. A paper that discussed momentum in bond markets, is the paper of Luu and Yu (2012).

In this paper, there was chosen to test time-series momentum instead of cross-sectional momentum, because from existing literature there could be concluded that time-series momentum is superior. Time-series momentum is an efficient method to predict patterns. An important role for tactical asset allocation is to understand which asset class will perform better "the next day". Which results in underweighting some asset classes and on the other side overweighting other asset classes. The trading signals that were used for the time-series momentum strategies were derived from cumulative past returns. The paper varied in both the number of months we lag returns to define the signals used to form the portfolio (the "look-back period") and the number of months each portfolio is held after it has been formed (the "holding period"). Four look-back periods (h): 1, 3, 6, and 12 were considered and four different holding periods (k) were studied: 1, 3, 6, and 12. Furthermore, in this thesis, the volatility scaling approach was used, due to the fact to the fact that recent papers concluded that time-series momentum is more successful when the volatility approach of Moskowitz, Ooi, and Pedersen (2012) is being used. In the volatility scaling approach, the weights across the assets are not constant, the weight of an asset is negatively related to volatility.

From the computed Sharpe ratios, there could be concluded that the strategies with a holding period of 1- or 3-months are most successful since most strategies with a holding period of 1- or 3-months gave a higher Sharpe ratio than the benchmark. These outcomes are in line with the paper of He & Li (2015), who also concluded that there is a profit opportunity for time-series momentum strategies with shorter holding periods and reversal with longer holding periods. Current literature about time-series momentum on bonds is very scarce. So an interesting conclusion that could be made is that for some strategy combinations time-series momentum can be successful for the asset class bonds. The use of time-series momentum also leads to some competitive Sharpe ratios for the asset class commodities. Especially, for the strategies with holding periods of 1- and 3-months competitive Sharpe ratios were found. The results are in line with the paper of Miffre and Rallis (2017). The results for currencies show that momentum strategies can be successful. Especially strategies with shorter holding periods give competitive Sharpe ratios for currencies. This outcome is in line with the evidence Moskowitz et al. (2012) provided. Overall, an important conclusion that can be made up from the computed Sharpe ratios is that rebalancing is very important. Time-series momentum strategies work better for shorter holding periods (1- and 3-months). Strategies with holding periods of 12 months all perform worse than the benchmark, so when a time-series momentum strategy is implemented an investor is better off by choosing for a shorter holding period. So momentum strategies are mainly effective with frequent rebalancing. The most profitable strategies have a holding period of 1- or 3-months.

From the computed alphas in table 2, we can conclude that for the asset classes' equity and bonds most strategies give a positive and significant annualized alpha, which indicates that the use of time-series momentum strategies leads to abnormal returns. For the asset classes' commodities and currencies, the strategies with holding periods of 6- and 12-months deliver negative and significant annualized alphas. So it is very important for an investor to frequently rebalance his or her portfolio, especially for the asset classes' commodities and currencies. Time-series momentum strategies work the best for the asset class equity since for equity the most positive and significant alphas were found. For the asset class equity, the annualized alpha reaches a value of 8.603% (a strategy with a look-back period of 6 months and a holding period of 6 months). In comparison with the study of Moskowitz et all. (2012) this study delivered a lower alpha.

7. Recommendation and limitations

The results show that time-series momentum strategies are the most effective with frequent rebalancing because the highest average Sharpe ratios are found for strategies with holding periods of 1- or 3-months (see table 1). Next to that, based on alpha as the performance measure, the use of time-series momentum strategies on commodities and currencies are only successful when an investor is frequently rebalancing. For the asset classes' commodities and currencies, the strategies with holding periods of 6- and 12-months deliver negative and significant annualized alphas, which indicates that the use of time-series momentum strategies leads to losses for the investor. So the recommendation for investors is to frequently rebalance their portfolio.

A potential limitation of the study is the fact that trading costs are not taken into consideration. If trading costs would be included, the returns of the time-series momentum strategies would be different. Furthermore, it will be interesting for future research to investigate what effect time-series momentum strategies have on other asset classes, like real estate for example.

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9. Appendix

Part A: Sharpe ratio

Table A1: Descriptive statistics of strategies with a holding period of 1 month

Reported are the annualized excess returns (%), the annualized volatilities (%), and the computed Sharpe ratios of the different asset classes. The period taken into consideration is 01.01.2002 till 31.12.2019. Competitive Sharpe ratios are given in bold.

Look-back period	Holding period	Asset classes	Annualized Excess Return (%)	Annualized Volatility (%)	Sharpe Ratio
1	1	**Equities**	0.89	17.50	0.05
		Bonds	-0.90	7.14	-0.13
		Commodities	0.96	14.76	**0.07**
		Currencies	0.27	10.11	0.03
3	1	**Equities**	5.98	17.42	**0.34**
		Bonds	1.91	7.12	0.27
		Commodities	6.86	15.89	**0.43**
		Currencies	6.19	9.96	**0.62**
6	1	**Equities**	7.24	17.39	**0.42**
		Bonds	1.36	7.13	0.19
		Commodities	5.97	15.92	**0.38**
		Currencies	4.04	10.46	**0.39**
12	1	**Equities**	2.24	17.49	0.13
		Bonds	2.74	7.10	**0.39**
		Commodities	0.61	16.00	**0.04**
		Currencies	1.41	10.11	**0.14**

Table A2: Descriptive statistics of strategies with a holding period of 3 months

Reported are the annualized excess returns (%), the annualized volatilities (%), and the computed Sharpe ratios of the different asset classes. The period taken into consideration is 01.01.2002 till 31.12.2019. Competitive Sharpe ratios are given in bold.

Look-back period	Holding period	Asset classes	Annualized Excess Return (%)	Annualized Volatility (%)	Sharpe Ratio
1	3	**Equities**	2.78	20.54	0.14
		Bonds	0.44	7.17	0.06
		Commodities	1.60	18.57	**0.09**
		Currencies	1.74	10.17	**0.17**
3	3	**Equities**	4.80	20.45	0.23
		Bonds	2.46	7.07	**0.35**
		Commodities	6.78	18.29	**0.37**
		Currencies	3.35	10.07	**0.33**
6	3	**Equities**	6.96	21.08	0.33
		Bonds	0.81	7.17	0.11

		Commodities	3.79	18.48	**0.21**
		Currencies	1.08	10.19	**0.11**
12	3	**Equities**	3.81	20.50	0.19
		Bonds	3.18	7.00	**0.45**
		Commodities	-1.39	18.57	-0.07
		Currencies	-3.13	10.08	-0.31

Table A3: Descriptive statistics of strategies with a holding period of 6 months

Reported are the annualized excess returns (%), the annualized volatilities (%), and the computed Sharpe ratios of the different asset classes. The period taken into consideration is 01.01.2002 till 31.12.2019. Competitive Sharpe ratios are given in bold.

Look-back period	Holding period	Asset classes	Annualized Excess Return (%)	Annualized Volatility (%)	Sharpe Ratio
1	6	**Equities**	2.82	24.25	0.12
		Bonds	-0.19	7.68	-0.02
		Commodities	-0.82	21.90	**-0.04**
		Currencies	1.37	10.75	**0.13**
3	6	**Equities**	2.71	24.26	0.11
		Bonds	1.08	7.63	0.14
		Commodities	2.55	21.86	**0.12**
		Currencies	1.73	10.72	**0.16**
6	6	**Equities**	6.75	23.87	0.28
		Bonds	0.97	7.67	0.13
		Commodities	-0.88	21.92	-0.04
		Currencies	-1.01	10.67	-0.09
12	6	**Equities**	4.45	24.04	0.19
		Bonds	2.93	7.40	**0.40**
		Commodities	-1.94	21.76	-0.09
		Currencies	-3.22	10.55	-0.31

Table A4: Descriptive statistics of strategies with a holding period of 12 months

Reported are the annualized excess returns (%), the annualized volatilities (%), and the computed Sharpe ratios of the different asset classes. The period taken into consideration is 01.01.2002 till 31.12.2019. Competitive Sharpe ratios are given in bold.

Look-back period	Holding period	Asset classes	Annualized Excess Return (%)	Annualized Volatility (%)	Sharpe Ratio
1	12	**Equities**	2.56	24.78	0.10
		Bonds	-0.09	7.58	-0.01
		Commodities	-2.11	21.52	-0.10
		Currencies	-0.95	9.83	-0.10
3	12	**Equities**	0.96	24.90	0.04
		Bonds	0.71	7.55	0.09
		Commodities	-2.56	21.47	-0.12
		Currencies	-0.87	9.84	-0.09

6	12	**Equities**	3.65	24.64	0.15
		Bonds	0.36	7.58	0.05
		Commodities	-3.56	21.32	-0.17
		Currencies	-2.86	9.45	-0.30
12	12	**Equities**	0.33	24.91	0.01
		Bonds	2.29	7.23	0.32
		Commodities	-3.92	21.26	-0.18
		Currencies	-2.47	9.56	-0.26

Table A5:Descriptive statistics of the benchmark for each asset class

Reported are the annualized excess returns (%), the annualized volatilities (%), and the computed Sharpe ratios of the different asset classes. The period taken into consideration is 01.01.2002 till 31.12.2019.

Asset classes	Annualized Excess Return (%)	Annualized Volatility (%)	Sharpe Ratio
Equities	4.82	14.67	0.33
Bonds	2.32	6.92	0.34
Commodities	-0.62	15.83	-0.04
Currencies	0.59	9.76	0.06

Part B: Alpha

The tables below describe per strategy the coefficients of the following regression: $r_t^{TSMOM(k,h)} = a + \beta 1 * MKT + \beta 2 * BOND + \beta 3 * GSCI + \beta 4 * USDX + \varepsilon$. In the regression, the equity benchmark is represented by the MSCI world index. The bond benchmark is represented by the US 10Y Govt Bond. Furthermore, the ISHARES S&P GSCI Commodity-index represents the commodity benchmark and the currency benchmark is represented by the US dollar index. Under the coefficients, the standard deviations are reported in brackets. The annualized alphas are expressed in percentage points. Furthermore, the R-squares are given in percentage points as well. TSMOM (k,h), stands for time-series momentum strategy with a look-back period of k and a holding period of h.

Table B1: TSMOM (1,1)

VARIABLES	TSMOM(1,1) EQ	TSMOM(1,1) BO	TSMOM(1,1) CO	TSMOM(1,1) CU
Equity	-0.163	0.086	-0.334	0.161
	(0.356)	(0.147)	(0.311)	(0.294)
Bonds	0.269	0.326	-0.631	0.093
	(0.647)	(0.267)	(0.565)	(0.535)
Commodities	-0.048	-0.063	0.410	-0.004
	(0.317)	(0.131)	(0.277)	(0.262)
Currencies	0.389	-0.030	-0.055	-0.688
	(0.530)	(0.219)	(0.463)	(0.439)
Alpha	2.534**	-1.579***	3.823***	2.289**
	(1.223)	(0.504)	(1.068)	(1.011)
Observations	215	215	215	215
R-squared	0.005	0.009	0.018	0.014

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B2: TSMOM (3,1)

VARIABLES	TSMOM(3,1) EQ	TSMOM(3,1) BO	TSMOM(3,1) CO	TSMOM(3,1) CU
Equity	0.422	0.013	-0.373	-0.090
	(0.365)	(0.142)	(0.363)	(0.211)
Bonds	0.155	0.198	-0.557	-0.138
	(0.664)	(0.259)	(0.660)	(0.384)
Commodities	0.355	0.068	0.168	-0.213
	(0.325)	(0.127)	(0.323)	(0.188)
Currencies	0.033	-0.238	0.038	0.235
	(0.544)	(0.212)	(0.541)	(0.315)
Alpha	5.134***	1.825***	4.765***	5.296***
	(1.254)	(0.489)	(1.246)	(0.725)

Observations	215	215	215	215
R-squared	0.028	0.008	0.007	0.009

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B3: TSMOM (6,1)

VARIABLES	TSMOM(6,1) EQ	TSMOM(6,1) EQ	TSMOM(6,1) CO	TSMOM(6,1) CU
Equity	-0.156	-0.073	0.171	-0.054
	(0.345)	(0.152)	(0.307)	(0.200)
Bonds	-0.018	-0.098	-0.746	0.856**
	(0.628)	(0.277)	(0.558)	(0.363)
Commodities	0.225	0.183	-0.470*	0.183
	(0.308)	(0.136)	(0.273)	(0.178)
Currencies	0.073	-0.406*	0.673	-0.258
	(0.515)	(0.227)	(0.457)	(0.298)
Alpha	5.427***	1.245**	5.990***	4.272***
	(1.187)	(0.523)	(1.054)	(0.686)
Observations	215	215	215	215
R-squared	0.003	0.024	0.026	0.034

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B4: TSMOM (12,1)

VARIABLES	TSMOM(12,1) EQ	TSMOM(12,1) BO	TSMOM(12,1) CO	TSMOM(12,1) CU
Equity	0.069	-0.198	-0.829**	-0.192
	(0.336)	(0.149)	(0.337)	(0.212)
Bonds	0.549	-0.135	-0.808	-0.309
	(0.612)	(0.271)	(0.612)	(0.386)
Commodities	-0.343	0.062	0.097	-0.082
	(0.300)	(0.133)	(0.300)	(0.189)
Currencies	-0.625	0.226	0.174	0.288
	(0.502)	(0.222)	(0.502)	(0.316)
Alpha	3.651***	2.338***	3.888***	1.960***
	(1.156)	(0.512)	(1.157)	(0.728)
Observations	215	215	215	215
R-squared	0.032	0.011	0.034	0.007

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B5: TSMOM (1,3)

VARIABLES	TSMOM(1,3) EQ	TSMOM(1,3) BO	TSMOM(1,3) CO	TSMOM(1,3) CU
Equity	0.401	-0.041	-0.602	-0.215
	(0.428)	(0.144)	(0.410)	(0.192)
Bonds	0.060	-0.056	0.003	0.345
	(0.778)	(0.262)	(0.747)	(0.349)
Commodities	0.294	-0.279**	0.346	0.135
	(0.381)	(0.128)	(0.366)	(0.171)
Currencies	-0.389	0.374*	0.722	0.258
	(0.638)	(0.214)	(0.612)	(0.286)
Alpha	3.127**	0.105	3.927***	1.846***
	(1.470)	(0.494)	(1.410)	(0.658)
Observations	215	215	215	215
R-squared	0.011	0.029	0.019	0.022

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B6: TSMOM (3,3)

VARIABLES	TSMOM(3,3) EQ	TSMOM(3,3) BO	TSMOM(3,3) CO	TSMOM(3,3) CU
Equity	0.690*	0.103	0.052	0.102
	(0.402)	(0.152)	(0.397)	(0.213)
Bonds	0.852	-0.354	-0.200	0.294
	(0.732)	(0.277)	(0.723)	(0.387)
Commodities	-0.222	-0.085	0.364	-0.175
	(0.358)	(0.136)	(0.354)	(0.190)
Currencies	-1.420**	0.084	0.098	0.437
	(0.600)	(0.227)	(0.592)	(0.318)
Alpha	4.541***	2.244***	6.668***	4.123***
	(1.383)	(0.523)	(1.365)	(0.732)
Observations	215	215	215	215
R-squared	0.038	0.015	0.011	0.019

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B7: TSMOM (6,3)

VARIABLES	TSMOM(6,3) EQ	TSMOM(6,3) BO	TSMOM(6,3) CO	TSMOM(6,3) CU
Equity	0.368	-0.181	-0.218	0.127
	(0.427)	(0.133)	(0.359)	(0.197)
Bonds	0.260	0.336	-0.196	0.023
	(0.776)	(0.242)	(0.653)	(0.358)
Commodities	0.188	0.065	-0.187	-0.236
	(0.380)	(0.118)	(0.320)	(0.175)

Currencies	-0.012	-0.006	0.184	0.567*
	(0.636)	(0.198)	(0.535)	(0.293)
Alpha	3.896***	0.277	3.609***	1.493**
	(1.467)	(0.457)	(1.233)	(0.676)
Observations	215	215	215	215
R-squared	0.010	0.028	0.005	0.028

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B8: TSMOM (12,3)

VARIABLES	TSMOM(12,3) EQ	TSMOM(12,3) BO	TSMOM(12,3) CO	TSMOM(12,3) CU
Equity	-0.167	0.200	0.276	-0.126
	(0.408)	(0.152)	(0.393)	(0.238)
Bonds	-0.744	-0.081	-0.302	-0.599
	(0.742)	(0.277)	(0.716)	(0.433)
Commodities	0.227	-0.135	0.319	0.144
	(0.363)	(0.135)	(0.350)	(0.212)
Currencies	-0.124	-0.205	-1.637***	-0.346
	(0.608)	(0.227)	(0.587)	(0.355)
Alpha	6.064***	3.093***	-3.717***	-2.531***
	(1.402)	(0.523)	(1.352)	(0.819)
Observations	215	215	215	215
R-squared	0.008	0.017	0.044	0.020

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B9: TSMOM (1,6)

VARIABLES	TSMOM(1,6) EQ	TSMOM(1,6) BO	TSMOM(1,6) CO	TSMOM(1,6) CU
Equity	0.114	0.212	-0.158	-0.169
	(0.561)	(0.155)	(0.452)	(0.209)
Bonds	-0.635	-0.382	-0.195	-0.841**
	(1.020)	(0.283)	(0.822)	(0.380)
Commodities	0.706	-0.071	-0.417	-0.202
	(0.500)	(0.139)	(0.403)	(0.186)
Currencies	-0.269	0.226	0.736	0.432
	(0.836)	(0.232)	(0.674)	(0.312)
Alpha	5.276***	0.749	0.093	1.958***
	(1.927)	(0.534)	(1.553)	(0.719)
Observations	215	215	215	215
R-squared	0.018	0.038	0.008	0.027

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B10: TSMOM (3,6)

VARIABLES	TSMOM(3,6) EQ	TSMOM(3,6) BO	TSMOM(3,6) CO	TSMOM(3,6) CU
Equity	-0.372	0.064	0.064	-0.400*
	(0.473)	(0.154)	(0.441)	(0.222)
Bonds	0.173	-0.187	0.230	0.311
	(0.861)	(0.280)	(0.802)	(0.403)
Commodities	-0.206	-0.060	-0.383	-0.226
	(0.422)	(0.137)	(0.393)	(0.197)
Currencies	0.704	-0.287	-0.524	0.490
	(0.706)	(0.230)	(0.657)	(0.331)
Alpha	5.896***	2.094***	5.956***	2.199***
	(1.626)	(0.529)	(1.515)	(0.762)
Observations	215	215	215	215
R-squared	0.009	0.018	0.016	0.045

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B11: TSMOM (6,6)

VARIABLES	TSMOM(6,6) EQ	TSMOM(6,6) BO	TSMOM(6,6) CO	TSMOM(6,6) CU
Equity	-0.373	-0.105	0.267	0.185
	(0.505)	(0.166)	(0.438)	(0.236)
Bonds	0.080	0.036	-0.784	-0.253
	(0.918)	(0.302)	(0.797)	(0.430)
Commodities	0.234	0.114	0.993**	0.145
	(0.450)	(0.148)	(0.390)	(0.210)
Currencies	0.475	-0.286	-0.100	0.105
	(0.753)	(0.248)	(0.653)	(0.352)
Alpha	8.603***	1.775***	-0.961	-2.567***
	(1.735)	(0.571)	(1.506)	(0.812)
Observations	215	215	215	215
R-squared	0.006	0.013	0.065	0.020

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B12: TSMOM (12,6)

VARIABLES	TSMOM(12,6) EQ	TSMOM(12,6) BO	TSMOM(12,6) CO	TSMOM(12,6) CU
Equity	-0.055	-0.092	-0.225	-0.286
	(0.504)	(0.158)	(0.463)	(0.209)
Bonds	0.638	0.491*	0.152	-0.609
	(0.918)	(0.287)	(0.842)	(0.380)
Commodities	-0.046	0.003	-0.212	0.227

	(0.449)	(0.141)	(0.412)	(0.186)
Currencies	0.500	0.082	-0.133	-0.001
	(0.752)	(0.235)	(0.690)	(0.311)
Alpha	4.455**	2.075***	-3.790**	-2.577***
	(1.734)	(0.543)	(1.591)	(0.718)
Observations	215	215	215	215
R-squared	0.006	0.023	0.008	0.022

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B13: TSMOM (1,12)

VARIABLES	TSMOM(1,12) EQ	TSMOM(1,12) BO	TSMOM(1,12) CO	TSMOM(1,12) CU
Equity	-1.143**	-0.100	0.522	-0.158
	(0.536)	(0.157)	(0.432)	(0.199)
Bonds	-1.351	-0.470	-0.380	-0.090
	(0.975)	(0.286)	(0.785)	(0.363)
Commodities	0.387	0.043	-0.653*	-0.380**
	(0.477)	(0.140)	(0.385)	(0.177)
Currencies	-0.013	0.118	0.148	0.688**
	(0.799)	(0.234)	(0.644)	(0.297)
Alpha	5.014***	0.938*	-3.331**	-1.371**
	(1.841)	(0.540)	(1.484)	(0.685)
Observations	215	215	215	215
R-squared	0.028	0.014	0.019	0.038

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B14: TSMOM (3,12)

VARIABLES	TSMOM(3,12) EQ	TSMOM(3,12) BO	TSMOM(3,12) CO	TSMOM(3,12) CU
Equity	0.316	0.026	-0.223	0.056
	(0.466)	(0.158)	(0.437)	(0.200)
Bonds	1.152	0.146	0.565	-0.020
	(0.849)	(0.287)	(0.795)	(0.364)
Commodities	-0.549	-0.051	-0.155	-0.444**
	(0.416)	(0.140)	(0.389)	(0.178)
Currencies	-0.282	0.114	-0.309	0.786***
	(0.695)	(0.235)	(0.652)	(0.298)
Alpha	4.705***	1.072**	-4.413***	-1.711**
	(1.603)	(0.542)	(1.502)	(0.688)
Observations	215	215	215	215
R-squared	0.022	0.004	0.014	0.047

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B15: TSMOM (6,12)

VARIABLES	TSMOM(6,12) EQ	TSMOM(6,12) BO	TSMOM(6,12) CO	TSMOM(6,12) CU
Equity	-0.678	-0.115	0.766	0.192
	(0.508)	(0.161)	(0.486)	(0.199)
Bonds	0.208	0.166	0.205	-0.085
	(0.923)	(0.293)	(0.884)	(0.361)
Commodities	-0.076	0.067	-0.191	0.153
	(0.452)	(0.143)	(0.433)	(0.177)
Currencies	1.315*	0.159	-0.703	-0.156
	(0.757)	(0.240)	(0.725)	(0.296)
Alpha	7.150***	0.948*	-5.623***	-3.114***
	(1.744)	(0.553)	(1.670)	(0.682)
Observations	215	215	215	215
R-squared	0.022	0.009	0.014	0.015

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table B16: TSMOM (12,12)

VARIABLES	TSMOM(12,12) EQ	TSMOM(12,12) BO	TSMOM(12,12) CO	TSMOM(12,12) CU
Equity	-0.594	0.028	-0.368	-0.129
	(0.541)	(0.148)	(0.423)	(0.205)
Bonds	-0.107	-0.659**	0.661	0.284
	(0.985)	(0.269)	(0.770)	(0.373)
Commodities	-0.827*	0.103	-0.453	0.283
	(0.482)	(0.132)	(0.377)	(0.182)
Currencies	0.845	-0.084	0.528	-0.552*
	(0.807)	(0.221)	(0.631)	(0.305)
Alpha	4.273**	2.653***	-4.645***	-2.326***
	(1.861)	(0.509)	(1.454)	(0.704)
Observations	215	215	215	215
R-squared	0.029	0.043	0.026	0.026

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Summary

1. Introduction

Is it possible for an investor to use time-series momentum strategies to generate competitive Sharpe ratios and abnormal returns, across asset classes? Momentum strategies have been a very controversial subject among academics and investors. The main research question of this thesis is: to what extent can time-series momentum strategies generate competitive Sharpe ratios and abnormal returns, across the four asset classes: equity, bonds, commodities, and currencies? The profitability of the time-series momentum strategies will be measured by two different performance measures, the Sharpe ratio, and alpha. The Sharpe ratio will be used as a tool to assess the performance of an asset class. The Sharpe ratio adjusts a portfolio's past performance, for the excess risk that was taken. The higher the Sharpe ratio is for an asset class the better the performance of this asset class is. Next to the Sharpe ratio, the alpha will be analyzed. Alpha will also be used as a measure of performance, it indicates whether a strategy has managed to beat the market return over a given period. The excess return of a strategy relative to the return of a benchmark index is the alpha.

Equity was the first asset class in which evidence for momentum was documented, this was done by Jegadeesh and Titman (1993). The method that was used in their paper became a very popular methodology for composing momentum portfolios. After the paper of Jegadeesh and Titman (1993), new papers about momentum strategies were published in which momentum was also documented for other asset classes. Erb & Harvey (2006) and Miffre & Rallis (2007) documented momentum effects for commodities. Furthermore, Menkhoff et al. (2012) documented momentum effects for the asset class currencies. Only for the asset class fixed income, there is almost no existing literature available. A paper that discussed momentum in bond markets, is the paper of Luu and Yu (2012).

Time-series momentum strategies are economically important because if investors can gain profit from time-series momentum strategies at the asset class level, this will result in higher financial benefits to investors than a regular buy and hold strategy. What element in this thesis goes beyond existing work? Existing studies that investigated momentum strategies are mostly about futures or focusing on one specific asset class, this study will investigate time-series momentum strategies for four different asset classes: equity, bonds, currencies, and commodities. Can the time-series momentum effect also be proven to exist within various other asset classes like bonds, commodities, and currencies? This will be investigated in this paper. Next to that, this paper also uses a different percentage for volatility scaling, than most existing papers. Most papers that documented time-series momentum used 40% in their formula for the volatility calculation, but this 40% is not based on anything. In this paper there is chosen to use the average volatility of the asset class as N. We will investigate if there are different results found with this method.

2. Data description

The dataset that is used in this paper consists of monthly prices of the following four asset classes: equity, bonds, currencies, and commodities. The data covered the period from 01.01.2002 till 31.12.2019. The prices for the four asset classes are denominated in dollars. The data that is used for the asset class equity is represented by the MSCI World index. The MSCI World index is an international equity index, which tracks stocks from 23 developed countries. The following developed countries are represented by the MSCI world index: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the UK, and the US. The choice for these equity markets is based on the paper of (Asness, Moskowitz, & Pedersen, 2013). The monthly prices of the equity indices are retrieved from Eikon. The data that represents the asset class bonds consists of the 10-year government bond from the US. Unfortunately, there was no access to get the data for the FTSE world government bond index, so there is chosen to use the data from the US. The data for these government bonds are retrieved from Eikon. The data that is used for the asset class commodities are represented by the ISHARES S&P GSCI Commodity index. The ISHARES S&P GSCI Commodity index seeks to track the results of a fully collateralized investment in futures contracts on an index composed of a diversified group of commodities futures. The data that is used for the asset class currencies consists of the spot exchange rates dollar and euro. The spot exchange rates are retrieved from Eikon. This study is about excess returns, the risk-free rate is needed to compute the excess returns. The 3-month U.S. Treasury Bill is considered as the risk-free rate for this study. The risk-free rate is downloaded from WRDS. The excess returns are computed by subtracting the risk-free rate from the return.

3. Time-Series Momentum Strategies – Methodology

Construction of the time-series momentum strategies

The trading signals that are used for the time-series momentum strategies are derived from cumulative past returns. If the cumulative past return is positive, the future returns are also expected to be positive because of the trend-following patterns. So this means that for a positive cumulative return, the market signal will be a "buy". When the cumulative past return is negative, the future returns are also expected to be negative. In this case, the market signal will be a "sell".

This study will vary in both the number of months we lag returns to define the signals used to form the portfolio (the "look-back period") and the number of months each portfolio is held after it has been formed (the "holding period"). Each strategy has a different look-back period and holding period. By changing these three elements, different trading strategies are formed. This study considers four different look-back periods (k): 1, 3, 6, and 12 months. The look-back period will indicate how many past months are included in the calculation of the cumulative returns. So, a look-back period of k implies that the cumulative returns are the sum of the past k returns. On the other hand, this study will also vary in the number of months the portfolio will be held. Four different holding periods (h) are taken into consideration: 1, 3, 6, and 12 months. The trading signal does not change during the holding period. The combination of the number of look-back periods and the number of holding periods will give 16 different strategies. The 16 strategies can be examined with two different approaches: with or without short-selling constraints. Going short on an asset could give an investor some extra profits, but on the other hand, short-selling also increases the overall risk of a portfolio. In this paper, all the strategies are considered with short-selling possibilities. The expectation is that momentum will perform better in the shorter holding periods, so the 1- and 3-month holding periods. This is because in these shorter holding periods the portfolio gets rebalanced frequently.

After the trading signals are computed for each asset class, the final portfolio is made. There will be four different portfolios: equity, bond, commodity, and currency. For building the portfolios, it is essential to give weights to all the assets. There are two approaches to give weights to the assets: the equally weighted approach and the volatility scaling approach that was used by the paper of Moskowitz, Ooi, and Pedersen (2012). This thesis will only investigate the volatility scaling approach, due to the fact to the fact that recent papers concluded that time-series momentum is more successful when the volatility approach of Moskowitz, Ooi, and Pedersen (2012) is being used. For example, the paper of Kim, Tse, and Wald (2016) confirms the choice for the volatility scaling approach: “Using TSMOM, the alphas of the individual contracts are on average 1.08%, the same as the portfolio alpha. However, if we use unscaled, equal-weighted returns, the portfolio alpha, and the average individual alpha drop to 0.39% and 0.40%, respectively.” So a volatility scaling approach seems to be superior to the equally weighted approach.

<u>Volatility scaling approach</u>

The volatility scaling approach that will be investigated is comparable to the approach of Moskowitz (2012). Moskowitz, Ooi, and Pedersen (2012) sized each position so it had ex-ante volatility of 40%. In this approach, the weights across the assets won’t be constant, the weight of an asset is negatively related to volatility. The size of a position increases (decreases) when the volatility of an asset is smaller (larger). The reason why there is chosen for this approach is that otherwise the analysis would be driven by high volatility asset classes. The strategy return for each asset will be determined as follows:

$$r_{t,t+h}^{TSMOM,s} = sign\left(r_{t-k,t^s}\right) * \frac{N\%}{\sigma_t^s} * r_{t,t+h^s}$$

Where $r_{t,t+h}^{TSMOM,s}$ represents the momentum strategy excess return of asset s at time t. k is the number of months considered as the look-back period and h is the number of months considered as the holding period. N% is the ex-ante volatility. Most papers that documented time-series momentum used 40% in their formula for the volatility calculation, but this 40% is not based on anything. In this paper it was chosen to use the average volatility of the asset class as N. We will investigate if there are different results found with this method.

$$\sigma_t^2 = 12 * \sum_{i=0}^{\infty} * (1-\theta) * \theta^i * (r - \bar{r}_t)^2$$

Where ${\sigma_t}^2$ represents the annualized variance for each asset class. The scalar 12 makes the volatility annual and Θ represents the rate of decay. The weights $(1-\theta) * \theta^i$ add up to one, and $\bar{r_t}$ is the exponentially weighted average return. The volatility model is the same for all assets at all times.

Every strategy will be tested on each asset class (equity, bond, commodity, and currency). The constructed strategies will be analyzed by two different performance measures. The Sharpe Ratio and alpha.

3.1. Performance Measure 1: Sharpe Ratio

The Sharpe ratio adjusts a portfolio's past performance, for the excess risk that was taken. The higher the Sharpe ratio is for an asset class the better the performance of this asset class is.

The Sharpe Ratio is calculated by dividing the average annualized excess return by the average annualized volatility. Where the volatility is the standard deviation of the returns.

$$Sharpe\ ratio = \frac{R_p - R_f}{\sigma_p}$$

Where, R_p is the return of portfolio, R_f is the risk-free rate and σ_p is the standard deviation.

3.2. Performance Measure 2: Alpha

The ability for an investor to get an additional return without increasing risk, cannot be measured with the Sharpe Ratio. To find out if this is possible we need to compute the alpha from a benchmark regression. Of course, it will be possible to increase the profitability of a portfolio by increasing risk, but that is not the purpose of this study. A standard approach that is being used in literature to adjust risk performance is to regress the returns of a certain strategy on the Fama-French 3 factor model. This study differentiates from this standard approach since this study is not only about equity, there are more asset classes involved. The factors SMB (small minus big) and HML (high minus low) will be excluded and some new factors will be added. SMB is a factor in the Fama/French pricing model that says smaller companies outperform larger ones over the long-term. HML is another factor in the model that says value stock tend to outperform growth stocks. Moskowitz et all. (2012) didn't find any significant betas for SMB or HML, that is the reason why this paper also excludes these factors.

Alpha is a term used to describe an investment strategy's ability to beat the market and it is often referred to as "excess return" or "abnormal rate of return", which refers to the idea that markets are efficient, so there is no way to systematically earn a return that exceeds the market. Alpha represents the performance of a portfolio relative to a benchmark, so alpha represents the extra value time-series momentum adds to the return. A positive and significant alpha would mean that the time-series momentum strategy provides an additional return. To evaluate the abnormal performance of the time-series momentum strategies, the alphas will be computed from the following regression:

$$r_t^{TSMOM(k,h)} = a + \beta 1 * \mathrm{MKT} + \beta 2 * \mathrm{BOND} + \beta 3 * \mathrm{GSCI} + \beta 4 * \mathrm{USDX} + \varepsilon,$$

where k is the look-back period and h the holding period. In the regression, the dependent variable is an excess return of the trading strategy with k look-back periods and h holding periods. The independent variables represent coefficients for the market factor (MKT), the bond index (BOND), commodity index (GSCI), and the currency index (USDX). These regressors are the times series of the chosen asset classes that are explained in chapter 3.

4. Time-Series Momentum Strategies – Results

4.1. Performance Measure 1: Sharpe Ratio – Results

The Sharpe ratio uses the standard deviation to measure the risk-adjusted returns for an asset. The greater the Sharpe ratio of an asset, the better its risk-adjusted-performance. A negative Sharpe ratio would indicate that either the risk-free rate is greater than the return of the asset, or the return of the asset is expected to be negative.

Intuitively, one could say that the Sharpe ratio of a risk-free asset is zero. So a positive Sharpe ratio would therefore indicate a higher reward for risk. The higher the Sharpe ratio, the better the investment looks from a risk/return perspective.

Table 1: Average Sharpe ratios for strategies with different holding periods

The period taken into consideration is 01.01.2002 till 31.12.2019.

Holding period (in months)	Asset Class	Average Sharpe ratio
1	Equities	0.24
1	Bonds	0.18
1	Commodities	0.23
1	Currencies	0.30

3	Equities	0.22
3	Bonds	0.24
3	Commodities	0.15
3	Currencies	0.08
6	Equities	0.18
6	Bonds	0.16
6	Commodities	-0.01
6	Currencies	-0.03
12	Equities	0.08
12	Bonds	0.11
12	Commodities	-0.14
12	Currencies	-0.19

The results in table 1 show that frequently rebalancing is very important. Strategies with shorter holding periods have a higher average Sharpe ratio compared to the strategies with longer holding periods. The highest Sharpe ratios are found for strategies with holding periods of 1 month and the lowest Sharpe ratios are found for strategies with holding periods of 12 months. For the Sharpe ratios, the significance is not taken into consideration, the formal significance test is only done for the annualized alphas.

An overview of the computed Sharpe ratios and the descriptive statistics per strategy are given in the appendix.

Results per asset class

Equity: The Sharpe ratio for the benchmark of equity is 0.33 (see table A5), a Sharpe ratio higher than 0.33 would indicate that momentum strategies are beneficial for the asset class equity. The strategy that gives the most competitive Sharpe ratio for equity, is a strategy with a look-back period of 6 months and a holding period of 1 month (see table A1).

Time-series momentum strategies provide competitive Sharpe ratios for the asset class equity, but only for shorter holding periods. For strategies with holding periods of 6- or 12 months, the results show a lower Sharpe ratio than the benchmark (see tables A3 & A4). The results for equity are in line with the paper of He & Li (2015), they also concluded that time-series momentum offers profit opportunity for strategies with shorter holding periods and tend to reverse for strategies with longer holding periods.

Bonds: The Sharpe ratio for the benchmark of bonds is 0.34 (see table A5), a Sharpe ratio higher than 0.34 would indicate that momentum strategies are beneficial for the asset class bonds. The strategy that gives the most competitive Sharpe ratio for bonds, is a strategy with a look-back period of 12 months and a holding period of 3 months (see table A2).

Current literature about time-series momentum on bonds is very scarce. An interesting conclusion that can be made is that for some strategy combinations time-series momentum can be successful for the asset class bonds. For example, the strategy with a look-back period of 12 months and a holding period of 3 months, gives a competitive Sharpe ratio of 0.45 (see table A2). But that are also quite some strategies that generate a lower Sharp ratio for bonds. This could be due to short-term return reversal. "Short-term reversal is the cross-sectional, negative relation between current stock returns and lagged returns", Kang, Khaksari & Nam (2018). The fact that, if a bond portfolio is giving negative past cumulative returns for some time, the returns could revert very quickly. This characteristic of bonds is not captured by time-series momentum strategies. Especially short positions could lead to potential losses, which hurts the returns of the bond portfolio.

Commodities: The Sharpe ratio for the benchmark of commodities is -0.04 (see table A5), a Sharpe ratio higher than -0.04 would indicate that momentum strategies are beneficial for the asset class commodities. The strategy that gives the most competitive Sharpe ratio for the asset class commodities, is a strategy with a look-back period of 3 months and a holding period of 1 month (see table A1).

The use of time-series momentum leads to some competitive Sharpe ratios for the asset class commodities, but only for time-series momentum strategies with shorter holding periods. Especially for the strategies with holding periods of 1-, 3- months successful Sharpe ratios are found (see tables A1 & A2). Similar results are found in the paper of Erb & Harvey (2006), who concluded that a momentum strategy with a 12-month ranking period and a 1- month holding period is profitable in commodity futures markets. The outcomes for commodities are also in line with the paper of Miffre and Rallis (2017). They found 13 momentum strategies that were profitable in commodity futures markets over horizons that range from 1 to 12 months. Miffre and Rallis stated that there is a short-term continuation and long-term reversal in commodity futures prices.

Currencies: The Sharpe ratio for the benchmark of currencies is 0.06 (see table A5), so a Sharpe ratio higher than 0.06 would indicate that momentum strategies are beneficial for the asset class currencies. The strategy that gives the most competitive Sharpe ratio for the asset class commodities, is a strategy with a look-back period of 3 months and a holding period of 1 month (see table A1).

The results show that momentum strategies can be successful for currencies. Especially strategies with shorter holding periods give competitive Sharpe ratios. This outcome is in line with the evidence Moskowitz et al. (2012) provided. They also concluded that time-series momentum strategies for currencies are profitable.

An important role in momentum strategies is rebalancing. Beforehand the expectation was that the strategies which are frequently rebalanced would have the highest Sharpe ratios. This is also the case. The results reported in table 1 show that time-series momentum strategies with a holding period of 1- and 3-months have on average the highest Sharpe ratios. The momentum strategies with a holding period of 12 months have on average the lowest Sharpe ratios.

The conclusion that can be made up from the results is that time-series momentum strategies deliver competitive Sharpe ratios, but there are strategies that provide a lower Sharpe ratio compared with the benchmark. The results show that time-series momentum strategies work better for shorter holding periods (1- and 3-months). Strategies with holding periods of 12 months all perform worse than the benchmark, so when a time-series momentum strategy is implemented one is better off by choosing for a shorter holding period. Momentum strategies are mainly effective with frequent rebalancing. The most profitable strategies have a holding period of 1- or 3-months.

These competitive Sharpe ratios are not the only advantage of time-series momentum. Time-series momentum also takes away some risk. For example, a crisis could occur, which would have a negative influence on the market. A momentum strategy would push the investor out of the market, it would prevent an investor from losses. When short-selling is used like in this study, an investor would sell losing assets in a crisis, which could provide high returns. So there can be concluded that next to the competitive Sharpe ratios, time-series momentum also takes some risks away from the investor.

4.2. Performance Measure 2: Alpha – Results

Alpha represents the performance of a portfolio relative to a benchmark, so alpha represents the extra value time-series momentum adds to the return. A positive and significant alpha would indicate that time-series momentum strategies provide additional returns. To evaluate the abnormal performance of the strategies, the alphas are computed from the following regression:

$$r_t^{TSMOM(k,h)} = a + \beta 1 * \text{MKT} + \beta 2 * \text{BOND} + \beta 3 * \text{GSCI} + \beta 4 * \text{USDX} + \varepsilon$$

In the regression, the equity benchmark is represented by the MSCI world index. The bond benchmark is represented by the US 10Y Govt Bond. Furthermore, the ISHARES S&P GSCI Commodity-index represents the commodity benchmark and the currency benchmark is represented by the US dollar index.

Table 2: Annualized alphas

The reported annualized alphas are computed from the following regression: $r_t^{TSMOM(k,h)} = a + \beta 1 * \text{MKT} + \beta 2 * \text{BOND} + \beta 3 * \text{GSCI} + \beta 4 * \text{USDX} + \varepsilon$. *In this regression, the equity benchmark is represented by the MSCI world index. The bond benchmark is represented by the US 10Y Govt Bond. Furthermore, the ISHARES S&P GSCI Commodity-index represents the commodity benchmark and the currency benchmark is represented by the US dollar index. The annualized alphas are expressed in percentage points. TSMOM(k,h), stands for time-series momentum strategy with a look-back period of k and a holding period of h.*

Strategy	Equities	Bonds	Commodities	Currencies
TSMOM (1,1)	2.534**	-1.579***	3.823***	2.289**
TSMOM (3,1)	5.134***	1.825***	4.765***	5.296***
TSMOM (6,1)	5.427***	1.245**	5.990***	4.272***
TSMOM (12,1)	3.651***	2.338***	3.888***	1.960***
TSMOM (1,3)	3.127**	0.105	3.927***	1.846***
TSMOM (3,3)	4.541***	2.244***	6.668***	4.123***
TSMOM (6,3)	3.896***	0.277	3.609***	1.493**
TSMOM (12,3)	6.064***	3.093***	-3.717***	-2.531***
TSMOM (1,6)	5.276***	0.749	0.093	1.958***
TSMOM (3,6)	5.896***	2.094***	5.956***	2.199***
TSMOM (6,6)	8.603***	1.775***	-0.961	-2.567***
TSMOM (12,6)	4.455**	2.075***	-3.790**	-2.577***
TSMOM (1,12)	5.014***	0.938*	-3.331**	-1.371**
TSMOM (3,12)	4.705***	1.072**	-4.413***	-1.711**
TSMOM (6,12)	7.150***	0.948*	-5.623***	-3.114***
TSMOM (12,12)	4.273**	2.653***	-4.645***	-2.326***

*** p<0.01, ** p<0.05, * p<0.1

The results show that for most strategies the annualized alpha is positive and significant, which indicates that the use of time-series momentum strategies leads to abnormal returns. Especially most strategies with holding periods of 1- and 3-months, give positive and significant annualized alphas. Furthermore, it is interesting to see that especially for the asset classes' commodities and currencies the strategies with holding periods of 6- and 12-months deliver negative and significant annualized alphas. So there can be concluded that it is very important for an investor to frequently rebalance his or her portfolio, especially for the asset classes' commodities and currencies. The use of time-series momentum strategies on commodities and currencies is only successful when an investor is frequently rebalancing. Otherwise, the use of time-series momentum strategies leads to losses for the investor. Strategies with a holding period of 12 months only show negative and significant alphas for commodities and currencies, which indicates a reversal in returns for these asset classes.

The results show that in most cases time-series momentum strategies are successful since most strategies deliver positive and significant annualized alphas. Time-series momentum strategies work the best for equity since for equity the highest positive and significant alphas are found. Bonds, commodities, and currencies also deliver some positive and significant alphas but in comparison with equity, these asset classes are underperforming.

For the asset class equity, the annualized alpha reaches a value of 8.603% (a strategy with a look-back period of 6 months and a holding period of 6 months). The bond's alpha reaches a value of 3.093% (a strategy with a look-back period of 12 months and a holding period of 3 months. For the asset class commodities, an annualized alpha of 6.668% is found (a strategy with a look-back period of 3 months and a holding period of 3 months). The alpha of currencies reaches an annualized alpha of 5.296% (a strategy with a look-back period of 3 months and a holding period of 1 month).

Moskowitz et all. (2012) found a significant alpha of 1.58% per month or 4.75% per quarter. So in comparison with the study of Moskowitz et all. (2012) this study delivers a lower alpha, this could be because in this study a lower N is used for the volatility calculation. Moskowitz et all. (2012) used an N of 40%, whereas in this study there is chosen to use the average volatility of each asset class as N.

More detailed results of the annualized alphas can be found in part B of the appendix. For each strategy, the coefficients of the regression, the standard deviations, and the R-squared are reported.

5. Conclusion

This study investigated to what extent time-series momentum strategies could generate competitive Sharpe ratios and abnormal returns, across the four asset classes: equity, bonds, commodities, and currencies. The profitability of the time-series momentum strategies was analyzed by their Sharpe ratios and alphas. Where the Sharpe ratio adjusted a portfolio's past performance, for the excess risk that was taken. The alphas indicated whether a strategy manages to beat the market return over a given period. Alpha represents the excess return of a strategy relative to the return of a benchmark index.

Momentum strategies have been a well-researched topic by academics and investors. Jegadeesh and Titman (1993) were one of the first authors who documented price continuation for the asset class equity and their method became a very popular methodology for composing momentum portfolios. Momentum strategies were also investigated for other asset classes. Erb & Harvey (2006) and Miffre & Rallis (2007) documented momentum effects for commodities. Furthermore, Menkhoff et al. (2012) documented momentum effects for the asset class currencies. Only for the asset class fixed income, there is almost no existing literature available. A paper that discussed momentum in bond markets, is the paper of Luu and Yu (2012).

In this paper, there was chosen to test time-series momentum instead of cross-sectional momentum, because from existing literature there could be concluded that time-series momentum is superior. Time-series momentum is an efficient method to predict patterns. An important role for tactical asset allocation is to understand which asset class will perform better "the next day". Which results in underweighting some asset classes and on the other side overweighting other asset classes. The trading signals that were used for the time-series momentum strategies were derived from cumulative past returns. The paper varied in both the number of months we lag returns to define the signals used to form the portfolio (the "look-back period") and the number of months each portfolio is held after it has been formed (the "holding period"). Four look-back periods (h): 1, 3, 6, and 12 were considered and four different holding periods (k) were studied: 1, 3, 6, and 12. Furthermore, in this thesis, the volatility scaling approach was used, due to the fact to the fact that recent papers concluded that time-series momentum is more successful when the volatility approach of Moskowitz, Ooi, and Pedersen (2012) is being used. In the volatility scaling approach, the weights across the assets are not constant, the weight of an asset is negatively related to volatility.

From the computed Sharpe ratios, there could be concluded that the strategies with a holding period of 1- or 3-months are most successful since most strategies with a holding period of 1- or 3-months gave a higher Sharpe ratio than the benchmark. These outcomes are in line with the paper of He & Li (2015), who also concluded that there is a profit opportunity for time-series momentum strategies with shorter holding periods and reversal with longer holding periods. Current literature about time-series momentum on bonds is very scarce. So an interesting conclusion that could be made is that for some strategy combinations time-series momentum can be successful for the asset class bonds. The use of time-series momentum also leads to some competitive Sharpe ratios for the asset class commodities. Especially, for the strategies with holding periods of 1- and 3-months competitive Sharpe ratios were found. The results are in line with the paper of Miffre and Rallis (2017). The results for currencies show that momentum strategies can be successful. Especially strategies with shorter holding periods give competitive Sharpe ratios for currencies. This outcome is in line with the evidence Moskowitz et al. (2012) provided. Overall, an important conclusion that can be made up from the computed Sharpe ratios is that rebalancing is very important. Time-series momentum strategies work better for shorter holding periods (1- and 3-months). Strategies with holding periods of 12 months all perform worse than the benchmark, so when a time-series momentum strategy is implemented an investor is better off by choosing for a shorter holding period. So momentum strategies are mainly effective with frequent rebalancing. The most profitable strategies have a holding period of 1- or 3-months.

From the computed alphas in table 2, we can conclude that for the asset classes' equity and bonds most strategies give a positive and significant annualized alpha, which indicates that the use of time-series momentum strategies leads to abnormal returns. For the asset classes' commodities and currencies, the strategies with holding periods of 6- and 12-months deliver negative and significant annualized alphas. So it is very important for an investor to frequently rebalance his or her portfolio, especially for the asset classes' commodities and currencies. Time-series momentum strategies work the best for the asset class equity since for equity the most positive and significant alphas were found. For the asset class equity, the annualized alpha reaches a value of 8.603% (a strategy with a look-back period of 6 months and a holding period of 6 months). In comparison with the study of Moskowitz et all. (2012) this study delivered a lower alpha.